

LITERATURE REVIEW ON FACIAL CODING

Avril Mauro, Eunseo Kwak, Tabitha Weidner, Aayush Tarahkia, & Anthony Giang

Background

Facial coding is the process of measuring and defining human emotion through facial expressions, focusing specifically on facial movement as responses to different stimuli. Facial coding utilizes algorithms to monitor changes in facial texture, shape, and competition, translating them into universal facial expressions.

By its own definition, facial coding is often rejected by psychologists for its attempt to claim that universal facial expressions even exist. The main pushback against this technology is its assumption that emotions can be detected through facial expressions at all – a notion that has been widely disputed and refused by researchers. Many of our research streams explore this limitation in combination with the impact of culture, context, and bias on facial expressions which bar researchers from accepting the ‘one size fits all’ approach often employed with facial coding technology.

Despite these critiques, facial coding is still supported by businesses and marketers today who utilize the technology to form an efficient and cost-effective method to gauge the potency of marketing campaigns. However, the sheer number of images needed to train facial coding algorithms and the ethicality of gathering such data presents important considerations for businesses to make.

These concerns are relevant to Emozo as facial coding technology is the heart of the platform, being used everywhere from the United States to China, which reinforces the reason to re-evaluate universal emotions before applying the platform to people of diverse cultures and backgrounds.

The table below summarizes our research streams and shows the key findings regarding facial expression, facial coding, and data collection.

Title	Author	Source	Question	Key Finding
Facial Expressions Do Not Reveal Emotions	Lisa Feldman Barrett	Scientific American	How accurate is Darwin's previous research and publications on universal emotional recognition/	Even though extremely outdated and proven to be inaccurate, facial mapping as defined by Charles Darwin's fundamental 1872 text are continuing to be used as validation for modern human expression and misleading researchers.
The Risks of Using AI to Interpret Human Emotions	Mark Purdy, John Zealley, and Omaro Maselli	Harvard Business Review	What are possible biases of AIs used to interpret emotions?	Biases that can occur are based on gender, age, culture, and others, and come from how the AI is trained and utilized. These biases impede the AI's ability to accurately collect emotional data.
Do not rely on facial expressions for how people are feeling	Not Specified	Economist	Are certain facial features consistently and directly linked to specific emotions?	Certain facial features, while often associating with certain emotions, frequently perform poorly in helping classify emotions from facial expressions.
Artificial Intelligence is Misreading Human Emotion	Kate Crawford	The Atlantic	Are human facial expressions universal?	Facial expressions are not universal and they are not easily linked to specific emotions.
Computers can't tell if you're happy when you smile	Angela Chen	MIT Technology Review	How accurate is facial expression recognition technology?	There is no such thing as a recognizable facial expression across all cultures. Research has shown that even if the person is not smiling, does not mean that they are unhappy.
The ethical questions that haunt facial-recognition research	Richard Van Noorden	Nature Publishing Group	Will the implementation of facial coding be ethical?	It is almost impossible to conduct wide image scraping while enforcing informed consent, or even using a large dataset of images, which is essential to conducting successful facial coding.
Interesting numbers: An ethnographic account of	Robert Cluley	Sage Journals	How come, despite the strong critique from psychologists and researchers, one of the	Facial coding data allows businesses to tell a story and gain unique insights on their customers in a more efficient alternative to

quantification, marketing analytics and facial coding data			rising marketing trends today involves facial coding to detect customer emotions?	self-reported likert scales.
Using computer-vision and machine learning to automate facial coding of positive and negative affect intensity	Nathaniel Haines, Matthew W. Southward, Jennifer S. Cheavens, Theodore Beauchaine & Woo-Young Ahn	The Public Library of Science (PLOS One)	How accurate is CVML/facial coding in comparison to human coders?	By using videos to identify the strength and intensity in changes of patterns of facial actions, they determined computer vision and machine learning (CVML) facial coding was as effective as, and more time-efficient than human coders.
Applications of Automated Facial Coding in Media Measurement	Daniel McDuff and Rana el Kaliouby	IEEE Xplore	How can we create a context in which facial coding becomes more accurate?	Creating normative distributions for the base rates of emotions by video category creates an environment in which facial coding becomes far more effective.
Why faces don't always tell the truth about feelings	Douglas Heaven	Nature	Why do facial expressions not really tell the truth about someone's feelings?	There has been recognition of the fact that facial expressions could translate a person's emotion, but as science and technology progress, scientists are starting to realize that facial expression does not always convey a person's feelings.

Critical Voices

The first five research streams all echo the same few critiques against facial coding. The biggest of those claims is that emotions cannot be identified through facial expressions alone. Oftentimes, humans themselves cannot decipher the emotions of others through images of faces either. It was hypothesized by American psychologist, Paul Ekman, that facial expressions are universal (Crawford, 1). Ekman and Wallace Friesen published the Facial Action Coding System (FACS) in 1978, which identified around 40 distinct muscular contractions on the face and treated the basic components of a facial expression as 'action units'. Despite FACS becoming a business success, scientists from a variety of fields became skeptical of its accuracy, poking

holes into Ekman's methodology and shedding light on the limitations of his algorithm, which was biased and ineffective with diverse populations.

The high variability of human facial features, combined with discrepancies in lighting, image quality, and facial positioning of photos used to train facial coding algorithms, have motivated many further studies to conclude that emotions cannot be detected from facial expressions reliably. Like Ekman's experiment, many applications of facial coding technology of the past employed a 'one size fits all' approach. This resulted in several shortcomings, due to the fact that emotions are not universal - they are largely influenced by different situations, cultures, and contexts. A person's true emotions aren't always outwardly shown, and even when they are, it is difficult to accurately pinpoint the correlation between certain expressions of specific emotions. A smile might mean a person is 'happy', but a frown is not so obvious. The inability to link specific emotions to certain facial muscle movements allows for a very ambiguous interpretation of emotional cues and often produces misleading results. Furthermore, even if a frown is detected, it could lead to a classification of anger, sadness, or a variety of other negative emotions. Facial expressions are often tied to certain emotions but are not always going to be associated with each other.

Research has shown that, on average, adults in urban cultures only scowl 30% of the time when they are angry. This is one example of why facial expression is an unreliable indicator of human emotions. Another example takes place in an experiment where participants were shown a photo of a man's bright red, screaming face. Most participants identified the man as angry, but when the photo is enlarged, it is revealed that he is a football player celebrating a goal. His angry-looking face was, in fact, a show of pure joy. There is no guarantee that when someone is showing their facial expression, they are expressing that emotion. The limitation here is that even

humans can not always accurately tell someone's emotions just by looking at their facial expressions, and to assume that the 'objectivity' of machines will be more successful is not well supported by previous studies.

Deep Dive Into Limitations

A major consideration in the ethicality of gathering images for facial coding is the way image collection prioritizes company over privacy and the representation of vulnerable groups in this data collection. One example of the ethical concerns regarding these training images is a database of more than 100M images of 100,000 celebrities and public figures put together by Microsoft in 2014. This database was the largest of its kind and, due to the severe backlash, was taken down soon after. Even without training algorithms based on these faces, it is concerning that the faces of many public figures are used without care to train algorithms they have no knowledge about.

The real issue begins when sets of images are being used for facial coding, as people's faces are actively being used to analyze and predict others' emotions. One simpler example of this was an online gallery from a San Francisco cafe, which held 12,000 images of customers at the cafe without their consent.

A severe example of this issue occurred in 2019 when researchers reached out to a publisher to retract a scientific paper, which was published in 2018 and trained algorithms to distinguish the faces of the Uyghur people through thousands of images, many pulled from secret surveillance cameras. This shows not only the risks of facial coding, but how it has already turned corrupt in the academic field. Uyghur Muslims have faced horrible conditions in 'work camps' and constant surveillance by the Chinese government, and likely had no idea their faces

were being trained to be recognized. If technology like this ever fell into the wrong hands, it would be extremely easy for corrupt governments to train such technology to identify groups of people that were deemed unfavorable and track them down.

Recent advancements in the field of Computer Vision have made collecting facial expression data easier; however, interpreting and using this data has proved to be a challenge. A study conducted by Daniel McDuff and Rana el Kaliouby aims to provide a context in which this data can become more useful and how to overcome common obstacles when developing facial coding software. They first elected to operate on a far larger dataset than seen before, taking 4 years to collect 2 million observations from media content around the world. Using a cloud-based framework and over 10,000 pieces of media content, the study collected data from over 500,000 respondents. Then, they constructed a normative distribution of base rates for behaviors by video ad category - arguing that this created a context with more accurate emotional classification.

There were “five facial action classifiers for coding: smile, eyebrow raise, eyebrow furrow, nose wrinkle and/or upper lip raise, and lip depressor actions. The classifiers consisted of four components: 1) face detection and tracking, 2) image feature extraction, 3) SVM classification, 4) post-processing" (McDuff, Kaliouby 4). 34 landmark points were identified on the face and scaled to 96x96 pixels for proper data collection. In the facial coding system FACS, each facial action classifier received a distinct definition connected to the movement of a specific facial feature.

The researchers built normative distributions for base rates for each category of videos, validating them through testing - yielding confirmation of the results. Some key takeaways that were made during this stage, were that longer videos often had better reactions due to a longer

development period. Additionally, viewers that may cover the camera or try to cheat, were accounted for. Factors such as race, age, or gender, were also reflected in the software's decisions. As more data is collected, normative values and baselines can be developed for each of these to make the classifying of emotions easier.

Research done by the editors of the Psychological Science in the Public Interest Journal stated that "there was little to no evidence that people can reliably infer someone else's emotional state from a set of facial movements." This indicates a lack of concrete proof regarding facial expressions as the only means to translate the emotions of a person. Despite recognizing that facial expressions could be translated into emotion, the progression of facial coding technology and science has led to the realization that facial expressions do not always convey a person's inward emotions.

Facial Coding in the Business World

Despite the widespread criticism aimed at facial coding technology, it has still appeared as a component in rising marketing trends. This was explored in an ethnographic study conducted by the analytics and insight team of a global marketing company dubbed 'Super' for anonymity (Cluley). Their experiment involved recording the faces of subjects from Super's target audience as they reacted to an advertisement and collected data on specific facial movements labeled as 'tracks' on a time-series plot. They only analyzed 'smile tracks' because a smile almost always guarantees a happy emotion, making it the least ambiguous facial expression in their dataset (Cluley). Assumptions like this are what drive facial coding data analysis, and while this is looked down upon by most psychologists and researchers, this type of high-level inference is key to business strategy.

The versatility of facial coding technology in regards to diverse populations and situations is where it seems to lose its traction in the psychology world. However, in the business world, relevant populations are more focused as they are narrowed down to target audiences. In that sense, an algorithm that may not be ‘one size fits all’ can be optimized to be a ‘one size fits one’ – one being the target audience of the user. Furthermore, facial coding takes the weight of quantifying one’s emotions out of the customer’s hands and even looks at emotions in varying degrees to the decimal (between 0 and 1 for example). This makes facial coding a more efficient, convenient, and cost-effective alternative than the previous method of self-reported Likert scales emotion identification which is prone to nonresponse bias from customers (Cluley).

What can be done with facial coding is its most ‘interesting’ factor. Facial coding data provides companies with leverage to gain perspective on their customers and tell a story to their audience in ways that cannot be achieved with other conventional data types.

Conclusion

As a vital tool in modern market research, facial coding is seen as a cost-efficient and easy-to-access method for collecting data on emotional responses. While facial coding is well-received in the business world for these reasons, the consensus from the scientific end is generally negative. Critiques of facial coding range from ethical issues surrounding the non-consensual gathering of source images used for program training, to harmful biases that could be taught to programs. The biggest critique of facial coding is that facial expressions are not the sole indicator of emotions. The ‘one size fits all’ approach to facial coding is a general framework which assumes everyone reacts in a similar fashion, without considering individual traits such as gender, age, and culture. Despite scientific studies concluding that, to a certain

degree, facial coding technology does work, the critiques indicate that our current technology cannot detect emotions with complete accuracy.

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